Application of a stochastic surplus production model (SPiCT) to produce MSY advice for *Nephrops* Stock in FU 26-27 (Western Galicia and Northern Portugal)

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Abstract

The Surplus Production in Continuous Time (SPiCT) model to produce MSY advice was proposed by ICES for a number of stocks in category 3 during the benchmark workshop WKMSYSPiCT in 2021. *Nephrops* in FU26-27 is one of them. Available data and exploratory runs with defaults priors were showed during the Data Evaluation Meeting celebrated in November 2020 for evaluate the appropriateness of data. Experts suggested using independent fishery data instead commercial CPUE or effort. In addition, they also recommended a spatial analysis from survey data obtained in FU26 and FU27 and explore as input a combined biomass index from the Spanish survey conducted in FU26 (SP-NSGFS-IBTS-Q4-FU26) and Portuguese survey in FU27 (PtGFS-WIBTS-Q4-FU27). Furthermore, stronger priors of the shape of the production model (n) and the initial biomass depletion (B/K) were also suggested to the model. This working document details tasks conducted and results obtained.

1. INTRODUCTION

The *Nephrop*s stock in FU 26 (Western Galicia) and FU 27 (Northern Portugal) are included within the ICES Division 9a (Figure 1). Although FUs 26 and 27 are different stocks, landings records are not differentiated prior 1996 and they are assessed together. *Nephrops* in FU26-27 is considered as a data-limited stock and it is classified as category 3.4.1. (ICES, 2012).

Nephrops is mainly caught in a mixed bottom-trawl fishery targeting different species such as hake, anglerfish or megrim. This species represents a minor percentage in the composition of total trawl landings and can be considered as by-catch although it is a very valuable species. Landings are reported by Spain and minor quantities by Portugal. The catches are taken by the Spanish fleets fishing on the Western Galicia (FU 26) and Northern Portugal (FU 27) fishing grounds and by the Portuguese artisanal fleet fishing with traps in FU 27. Since 1990 onwards there has been a marked downward trend in landings. Available time series starts in 1975 with records of 622 t, being below 50 t for the 2005-2011 periods and below 10 t in 2012. Landings were minimal since that date (mean value 4 t) (ICES, 2020). Fishing effort and commercial CPUE also show a decreasing trend during the time series (ICES, 2020). The status of this stock is undesirable and it is considered a stock with an extremely low biomass (ICES, 2012). Last advice was zero catch and valid for 2020, 2021 and 2022 (ICES, 2019).

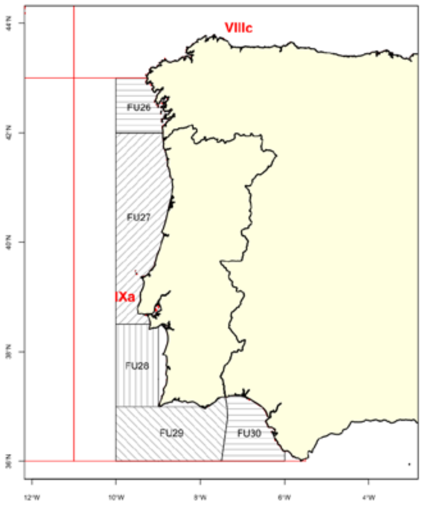


Figure 1. ICES Division 9a and *Nephrops* Functional Units (FUs). FU26 (Western Galicia) and FU27 (Northern Portugal).

Available data for FU26-27 includes landings, commercial effort and CPUE, as well as fishery independent information from IBTS surveys carried out in FU26 (West of Galicia) by IEO and in FU27 (North of Portugal) by IPMA. Discards are considered negligible. SPiCT exploratory runs using defaults priors were conducted during the Data Compilation Meeting in November 2020 (WKMSYSPiCT, WD: Vila, 2020). Those showed that when CPUE and effort are separately used as inputs in the model, some violations of the model assumptions based on-step-ahead residuals were observed. Additionally, non convergence of the retrospective analysis was found and stochastic reference points could not be derived. The model converged when IBTS survey index in FU26 (SP-NSGFS-IBTS-Q4-FU26) and in FU27 (PtGFS-WIBTS-Q4-FU27) were used as inputs, but results were not appropriated. The main issues were the huge uncertainty, problems with the production curve and the strong tendency in the retrospective pattern.

The IBTS surveys indices in FU26 and FU27 used in the model were estimated as the *Nephrops* mean weight from hauls conducted within statistics rectangles located in each FU. This estimation was not considered appropriated because depth was not taken into account and the quality of the index was questioned. Experts recommended carrying out a spatial-temporal analysis from the surveys information in FU26 (SP-NSGFS-IBTS-Q4) and FU27 (PtGFS-WIBTS-Q4) and to obtain and combined biomass index for FU26-27 stock. Besides, they recommended using stronger priors related to the shape of the production model (n) and the initial biomass depletion (B/K).

This working document details the work carried out in order to improve the biomass index from surveys, as well as, the results obtained from the application of the Surplus Production in Continuous Time (SPiCT) model (Pedersen and Berg, 2017) to produce MSY advice for *Nephrops* FU26-27 stock following the experts' recommendations.

2. TASKS CONDUCTED AFTER RECOMMENDATIONS GIVEN IN THE DATA COMPILATION MEETING

2.1. Average Stratified survey Index estimate for FU 26-27 from the Spanish and Portuguese IBTS survey carried out in FU 26 and FU 27, respectively

The Sp-NSGFS-IBTS-Q4 covers the northern Spanish shelf comprised in ICES Division 8c and the northern part of 9a, including the Cantabrian Sea and off Galicia waters. This survey usually starts at the end of the 3rd quarter (September) and finishes in the 4th quarter. Time series is available for 1984-2019 period. No survey was carried out in 1987. It is a bottom trawl survey with a random stratified by depth strata sampling design. Total area is divided in 5 sectors (Miño-Finisterre, Finisterre-Estaca, Estaca-Peñas, Peñas-Ajo and Ajo-Bidasoa) (Figure 2). Miño-Finisterre sector corresponds to statistics rectangles that compound *Nephrops* FU 26 stock (Western Galicia). The area of this sector is 4 327 Km^2. Therefore, hauls conducted in this sector can be used to derive a biomass index in this FU taken into account depth stratification (70-120 m, 121-200 m, 201-500m, 501-800m). Prior 1997, the lowest stratum covered since 30 m depth. However, hauls at depth lower than 70 m were not used as *Nephrops* is not distributed at this deep.

Portuguese survey (PtGFS-WIBTS-Q4) is carried out in Portuguese continental waters in the 4th quarter of the years. *Nephrops* data are available for 1984-2017 periods. No survey could conduct last two years. Survey extends from latitude 41°20' N to 36°30' N (ICES Division 9a) and from 20–750 m depth following 20-100 m, 101-200 m, 201-500 m and 501-750 m strata design. This survey is divided in 11 sectors (Figure 2), 6 of them correspond to FU 27 (Caminha, Matosinhos, Aveiro, Figueira, Berluga and Lisbon) covering a total area of 19 055 Km^2. So, hauls conducted in those sectors can be used to derive a stratified index in this FU.

A new depth stratified biomass index for the total area covering FU26-27 (23 382 Km^2) was estimated considering the following sectors: Miño-Finisterre (GAL), Caminha (CAM), Matosinhos (MAT), Aveiro (AVE), Figueira (FIG), Berluga (BER) and Lisbon (LIS), as parts of a unique survey and taking into account the area corresponding to each stratum of depth. *Nephrops* weight by haul was standardized to 1 hour. Figure 3 shows the new stratified biomass index obtained in FU26 (Western Galicia), FU27 (Northern Portugal) and FU26-27 (whole area covering these stocks).

Below are shown the expressions for the estimation of the average stratified index and their variance:

$$\overline{Y}_{st} = \frac{1}{A} * \sum A_h * \overline{Y}_h \qquad S^2(\overline{Y}_{st}) = \frac{1}{A^2} * \sum \frac{A_h^2 * S_h^2}{n_h}$$

where:

Y_{st} = Stratified mean catch
$S^2(Y_{st})$ = stratified variance
A = Total area
A_h = stratum area
Y_h = Mean Catch by haul in each stratum
n_h = Number of hauls in each stratum
S^2_h = Variance in each stratum

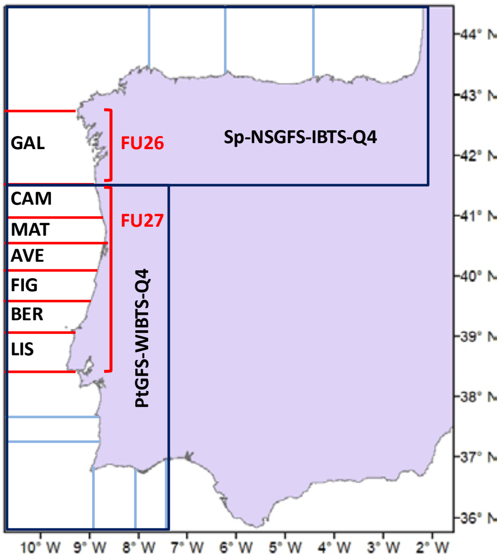
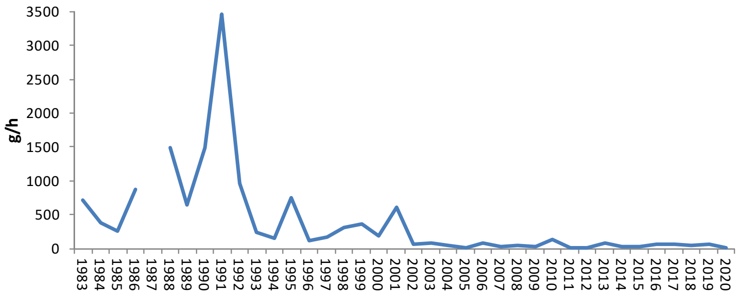
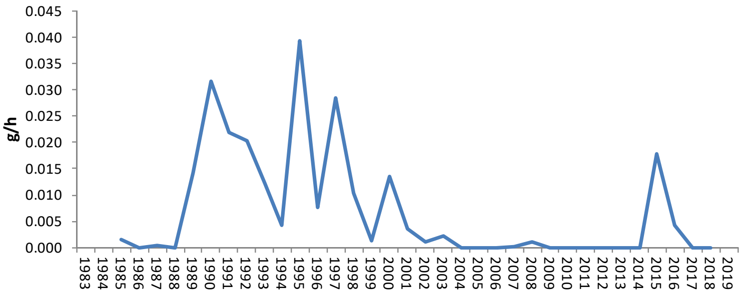


Figure 2. Area and different sectors covered by Spanish IBTS survey (Sp-NSGFS-IBTS-Q4) and Portuguese IBTS survey (PtGFS-WIBTS-Q4). Sectors in red correspond to FU26 (GAL) and FU27 (CAM, MAT, AVE, FIG, BER, LIS).





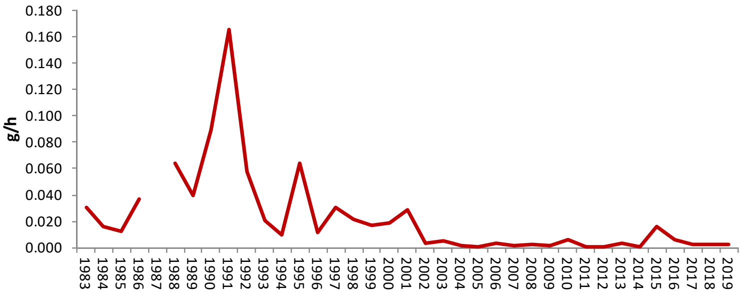


Figure 3. New stratified by depth biomass index in FU26 (above), FU27 (middle) and FU26-27 (below).

2.2..Spatial analysis from the Spanish and Portuguese IBTS survey carried out in FU 26 and FU 27, respectively

The *Nephrops* spatial distribution from Spanish survey in FU26 and Portuguese survey in FU27 for the all time series (1983-2019) is shown in Figure 4. *Nephrops* is mainly distributed in Miño-Fisnisterre sector (GAL) in FU26 from about 100 to 700 m depth and Caminha sector (CAM) in the north part of FU27 from 100 to 500 m depth. In the rest of the FU27, *Nephrops* patches occur particularly in Figueira sector (FIG) in the deepest stratum and Berluga sector (BER) in a higher bathymetric range. In Lisbon sector (LIS), *Nephrops* is present in a small patch in front of Cascais about 350 m depth.

A picture of the spatial distribution of *Nephrops* biomass index in FU26-27 for some years of the time series is shown in Figure 5 indicating a declining trend of the biomass index since 1983, as well as, of the *Nephrops* patches in FU26-27.

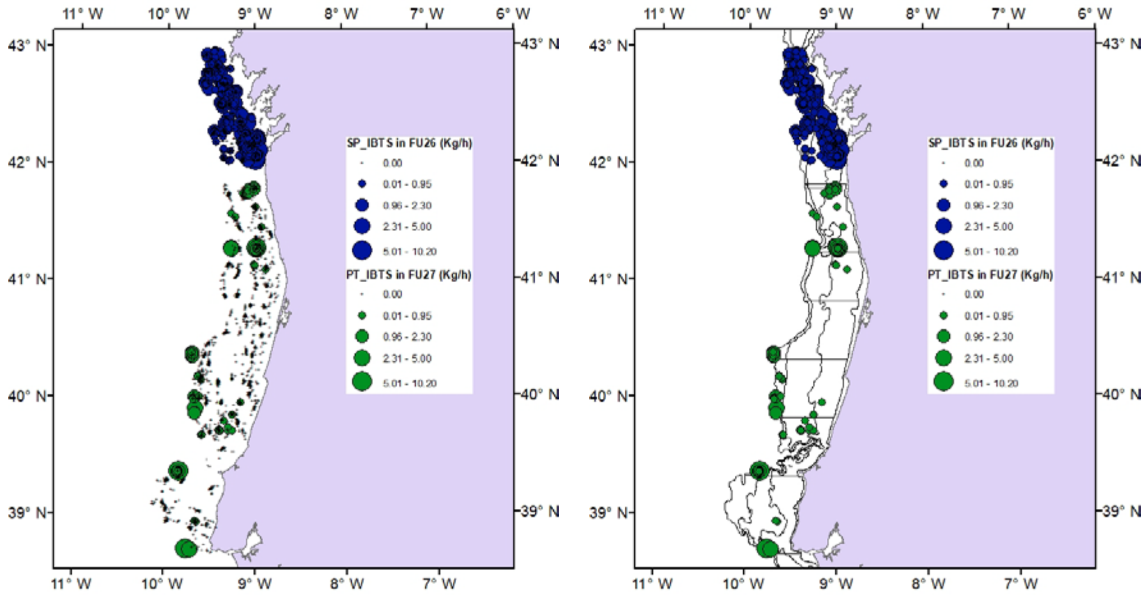


Figure 4. Spatial distribution of the *Nephrops* biomass index in FU26-27 (1983-2019) from the Spanish and Portuguese IBTS survey in FU26 and in FU27, respectively. Including hauls with zero *Nephrops* caught (left) and including bathymetry (right).

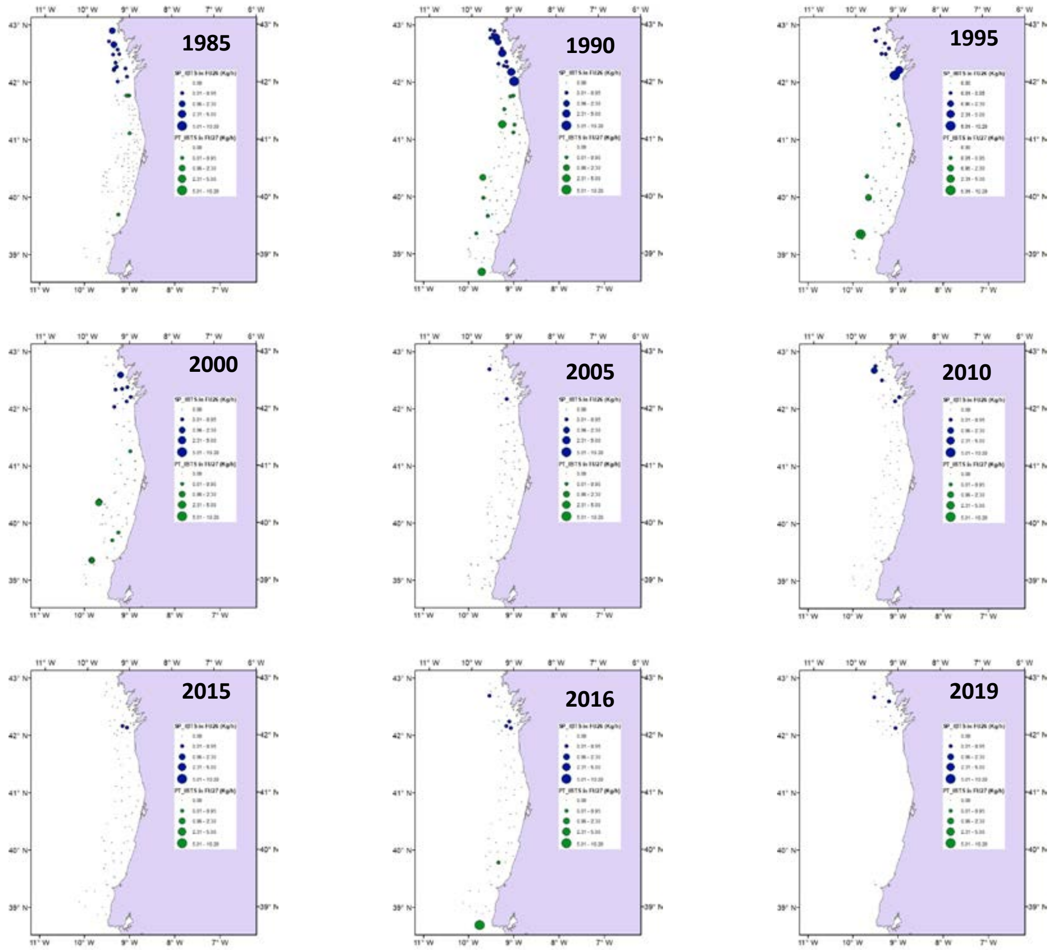


Figure 5. Spatial distribution of the *Nephrops* biomass index in FU26-27 for some years of the time series.

2.3. Spatial-temporal model for the Spanish and Portuguese IBTS survey index carried out in FU 26 and FU 27, respectively: New combined index estimation

In order to obtain a combined index for *Nephrops* in FU26-27 stock, a Bayesian hierarchical model was used. In particular the biomass index from Spanish survey in Fu26 and Portuguese survey in FU27 were used as response variables, while the bathymetry of the fishing haul, the time of the fishing haul and the geographical position (latitude and longitude) were included as explicative variables. Bathymetry was modelled as second random walk effect and the time and the geographical position as continuous variables. In addition, an autoregressive temporal component (AR1) was used to model the year of the survey. Finally, a survey random effect was added to account for the different survey catchability (e.g. gear, vessel, etc).

Response variables were log-transformed before being used in the model to reduce variability and to meet the theoretical assumptions of the model (e.g. normality and homoscedastic variance).

Models were fitted using the integrated nested Laplace approximation approach INLA (Rue et al., 2009) in the R software (R Core Team, 2019). Default INLA priors were used for the all the parameters.

Models were selected by testing all possible variables combination using the Watanabe Akaike information criterion (WAIC) (Watanabe, 2010) for goodness of fit and the log-conditional predictive ordinates (LCPO) (Gneiting and Raftery, 2007) for predictive quality measures, based on a leave-one-out cross-validation. WAIC and LCPO scores are inversely related to the compromise between fit, parsimony and predictive quality, i.e., lower scores denote better models.

For a first exploratory analysis it was possible to see that the Spanish survey caught much more *Nephrops* that the Portuguese one as previously has been noted in this WD (Figure 1).

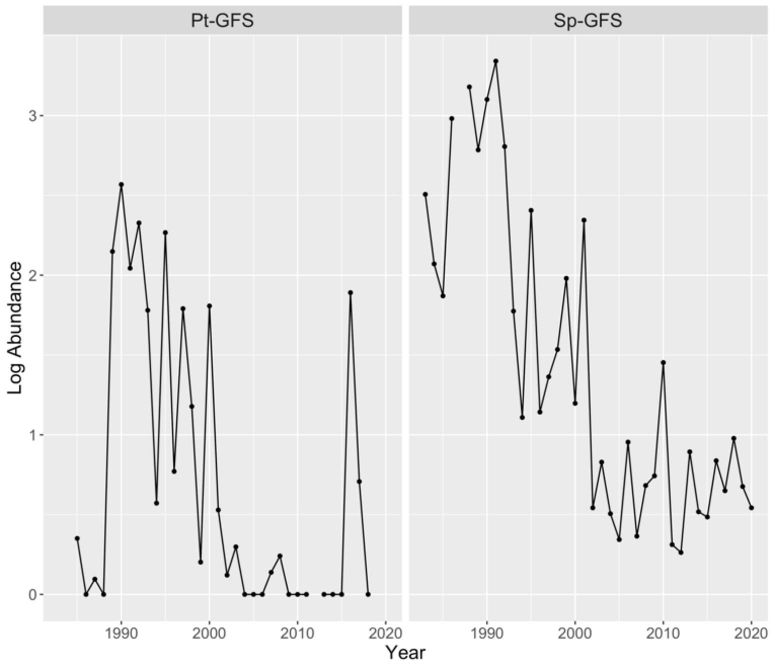


Figure 6. Log-transformed biomass index in kg/h for the historical series for the Portuguese (Pt-GFS) and Spanish (Sp-GFS) index.

The final model selected for the lowest WAIC and LCPO values, was the one that included the bathymetry as explicative variables, jointly with the survey random effect and the AR1 effect of the year. The others variables were removed subsequentially from the model as the WAIC and LCPO values were higher. Overall the model converged without any issue. The bathymetry showed a domeshaped mean functional response as showed in Figure 7.

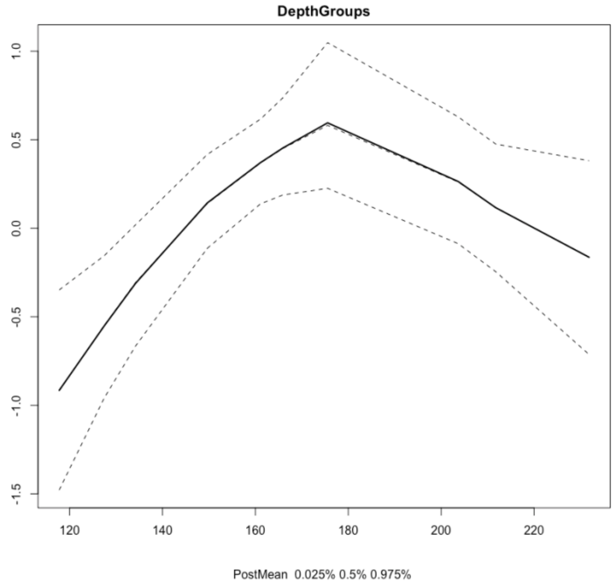


Figure 7. Second random walk effect for the bathymetry variable

The combined index for this *Nephrops* stock in FU26-27 is represented in Figure 8.

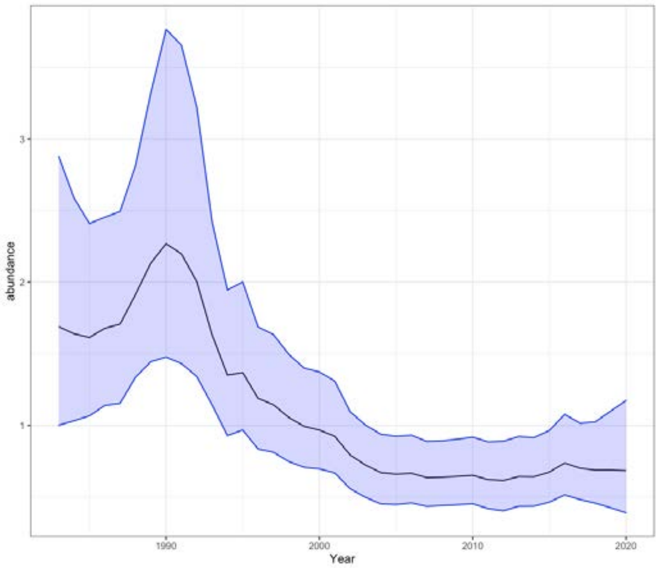


Figure 8. Combined index for *Nephrops* in FU26-27 derived from the Bayesian model

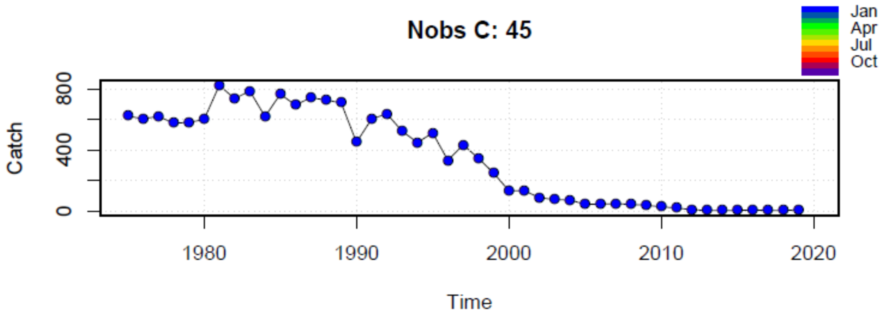
2.4. Exploratory assessment using SPiCT

Input data

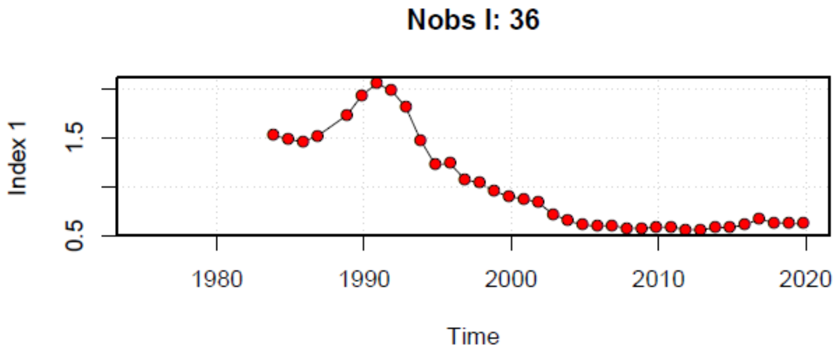
Landings from 1975 to 2019 and a fishery independent biomass index from 1983-2019 (there was not survey in 1987) were used as input data in the SPiCT model. Biomass indices considered were:

1. New combined biomass index for FU26-27
2. Stratified biomass index for FU26-27
3. Stratified biomass index for FU26

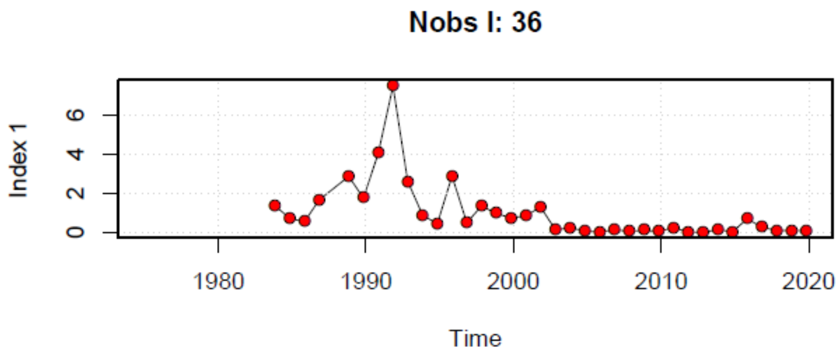
Landings



1. **New combined biomass index for FU26-27**



2. **Stratified biomass index for FU26-27**



3. **Stratified biomass index for FU26-**

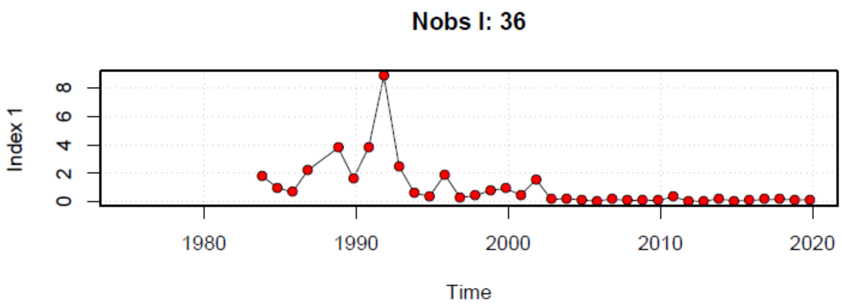


Figure 6. Input data for SPiCT considering the only one biomass index in each scenario.

Three scenarios were considered depend on the biomass index used:

- **Scenario 1:** Landings FU26-27 + New combined biomass index for FU26-27
- **Scenario 2:** Landings FU26-27 + Stratified biomass index for FU26-27
- **Scenario 3:** Landings FU26-27 + Stratified biomass index for FU26

Settings and priors

For all scenarios:

a) the biomass index time series was scaled to mean 1 in order to obtain a better numerical stability

```
mstd <-function(x) x/mean(x,na.rm=TRUE)
data$DEM = mstd(data$DEM)
```

b) An extra uncertainty was applied to landings from 1975 to 1980 as during this period is possible that a wrong gear identification of some trips could occur and as consequence *Nephrops* landing were lower.

```
inp$stdevfacC <- rep(1, length(inp$obsC))
inp$stdevfacC[1:6] <- 3
```

c) Moreover, the uncertainty of the survey index for 1983-1990 was also increased.

```
inp$stdevfacI <- list(c(rep(2, 7), rep(1, length(inp$timeI[[1]]) - 7)))
```

d) Different runs were conducted setting the prior for the parameter (logn) which determining the shape of the production curve.

Three options were tested:

1. Fixing logn=2
2. Fixing initial value of logn=2
3. Using the Tighter Shaefer prior for logn

e) The prior for the initial depletion level (logbkfrac) was also used. There is not an exact knowledge about the exploitation level before the beginning of the available landings data. Nevertheless, *Nephrops* always has been a valuable resource in this area and a target species at the beginning of the time series. So, it is probably that there was exploitation previously to 1975 at least medium.

f) In order to decrease the confidence intervals of the results, priors for the observation error of (logsdf) and (logsdc) were used in runs X.1. Priors for the ratios of process to observation errors (logalpha) and (logbeta) were removed as it is required.

Table 1 shows the different runs carried out and priors used.

Table 1. Runs and priors used related to the shape of the production curve (n), the exploitation level (B/K) and priors for the observation error term of and landings.

		RUN 1	RUN 1.1	RUN 2	RUN 2.1	RUN 3	RUN 3.1
SHAPE of the production curve	inp$logn=2	X	X				
	inpinilogn <- log(2); inp$phases$logn <- -1			X	X		
	inp$priors$logn <- c(log(2),0.5,1)					X	X
Initial DEPLETION level prior (B/K)_Medium Level	inp$priors$logbkfrac <-c(log(0.5),1,1)	X	X	X	X	X	X
Others Priors	inp$priors$logalpha <- c(0,0,0)		X		X		X
	inp$priors$logbeta <- c(0,0,0)		X		X		X
	inp$priors$logsdf <- c(log(3), 0.5, 1)		X		X		X
	inp$priors$logsdc <- c(log(0.1), 0.2, 1)		X		X		X

The checklist for acceptance of a SPiCT model was followed (Mildenberg, et al., 2020)

Results

The model did not converge with any combination of the setting priors when the **Scenario 1** was tested.

Similar results were obtained in **Scenario 2** and **Scenario 3**. The model converged in all runs and stochastics reference points were derived. However, better results were obtained when the logalpha and logbeta priors were removed of the model and priors logsdf and logsdc were applied (RUN 1.2, RUN 2.2 and RUN 3.2).

Nevertheless, the retrospective pattern showed consistence in Scenario 2 only when a number of years equal to three was used (retro (n=3)). Only retrospective to five years (retro(n=5)) in RUN1.1. converged. Monh's Rho value never was achieved for Scenario 3 in any run. See Table 2.

All variance parameters of the model were finite. Regarding to the standard diagnostics, for landings and biomass index, the mean of the one-step-ahead residuals was different from zero, there was not empirical autocorrelation in the residuals, and the residuals were normally distributed. So, no violations of the assumptions of the model were observed for any run.

The shape of the production curve was realistic, with Bmsy/K value between 0.5 and 0.7.

The assessment uncertainty analysis showed the confidence intervals for B/Bmsy and F/Fmsy ranging between 1 and 2 order of magnitude depending on the scenario and run.

Table 2 summaries the checklist for the different scenarios and runs.

Plots and tables for the SPiCT model obtained for Scenario 2 and RUNS X.1 applying priors **for** the observation error term are only shown in this WD.

Data, R file with code and results for different scenarios and runs are available on the sharepoint WKMSYSPiCT ("Personal folders/nep.fu.2627_Yolanda/Benchmark_FEB2021").

Table 2. Checklist of the model for the three scenarios.

	SCENARIO 1					
	RUN 1	**RUN 1.1**	**RUN 2**	**RUN 2.1**	**RUN 3**	**RUN 3.1**
Convergence	No converge	No converge	No converge	No converge	No converge	No converge

	SCENARIO 2					
	RUN 1	**RUN 1.1**	**RUN 2**	**RUN 2.1**	**RUN 3**	**RUN 3.1**
Convergence	YES	YES	YES	YES	YES	YES
Parameters variance finite	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Model assumption_Diagnosis	OK	OK	OK	OK	OK	OK
Retrospective pattern	OK (retro n=3)	OK	OK (retro n=3)	OK (retro n=3)	OK (retro n=3)	OK (retro n=3)
Monh's Rho (retro 5)	NAN	Monh's Rho <= 1	NAN	NAN	NAN	NAN
Monh's Rho (retro 3)	Monh's Rho < 1	Monh's Rho < 1	Monh's Rho < =1	Monh's Rho < 1	Monh's Rho <= 1	Monh's Rho < 1
Production curve	0.5	0.7	0.5	0.5	0.5	0.5
Sensitivity to initial values	NULL	NULL	NULL	NULL	NULL	NULL
Uncertainty-order magnitud						
B/Bmsy	2	1	2	1	2	1
F/Fmsy	2	2	2	1	2	1

	SCENARIO 3					
	RUN 1	**RUN 1.1**	**RUN 2**	**RUN 2.1**	**RUN 3**	**RUN 3.1**
Convergence	YES	YES	YES	YES	YES	YES
Parameters variance finite	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
Model assumption_Diagnosis	OK	OK	OK	OK	OK	OK
Retrospective pattern	Not consistent	Not consistent	Not consistent	Not consistent	Not consistent	Not consistent
Monh's Rho (retro 5)	NAN	NAN	NAN	NAN	NAN	NAN
Monh's Rho (retro 3)	NAN	NAN	NAN	NAN	NAN	NAN
Production curve	0.49	0.7	0.5	0.5	0.5	0.6
Sensitivity to initial values	NULL	NULL	NULL	NULL	NULL	NULL
Uncertainty-order magnitud						
B/Bmsy	2	1	2	2	2	1
F/Fmsy	3	2	2	1	2	1

Table 3. Results SPiCT model for Scenario 2 y RUN 1.1.

SCENARIO 2 RUN 1.1				
Summary estimates				
	estimate	**cilow**	**ciupp**	**log.est**
alpha	153.69	0.33	72445.04	5.03
beta	0.18	0.11	0.29	-1.73
r	0.55	0.07	4.11	-0.6
rc	0.21	0.06	0.78	-1.54
rold	0.13	0.03	0.52	-2.01
m	478.9	255.73	896.84	6.17
K	6646.9	3220.32	13719.51	8.8
q	0	0	0	-7.07
n	5.1	1.04	24.95	1.63
sdb	0.01	0	2.55	-5.21
sdf	0.51	0.39	0.66	-0.67
sdi	0.84	0.66	1.06	-0.18
sdc	0.09	0.06	0.13	-2.4
Stochastic Reference Points				
	estimate	**cilow**	**ciupp**	**log.est**
Bmsys	4466.83	2067	9652.92	8.4
Fmsys	0.11	0.03	0.39	-2.23
MSYs	478.72	255.63	896.5	6.17
State				
	estimate	**cilow**	**ciupp**	**log.est**
B_2019.94	181.84	84.72	390.31	5.2
F_2019.94	0.05	0.02	0.13	-2.97
B_2019.94/Bmsy	0.04	0.01	0.12	-3.2
F_2019.94/Fmsy	0.48	0.1	2.29	-0.74
Predictions				
	prediction	**cilow**	**ciupp**	**log.est**
B_2021.00	198.45	85.85	458.74	5.29
F_2021.00	0.05	0.01	0.2	-2.97
B_2021.00/Bmsy	0.04	0.01	0.16	-3.11
F_2021.00/Fmsy	0.48	0.07	3.12	-0.74
Catch_2020.00	9.71	4.39	21.48	2.27
E(B_inf)	5906.53	NA	NA	8.68

SCENARIO 2
RUN 1.1

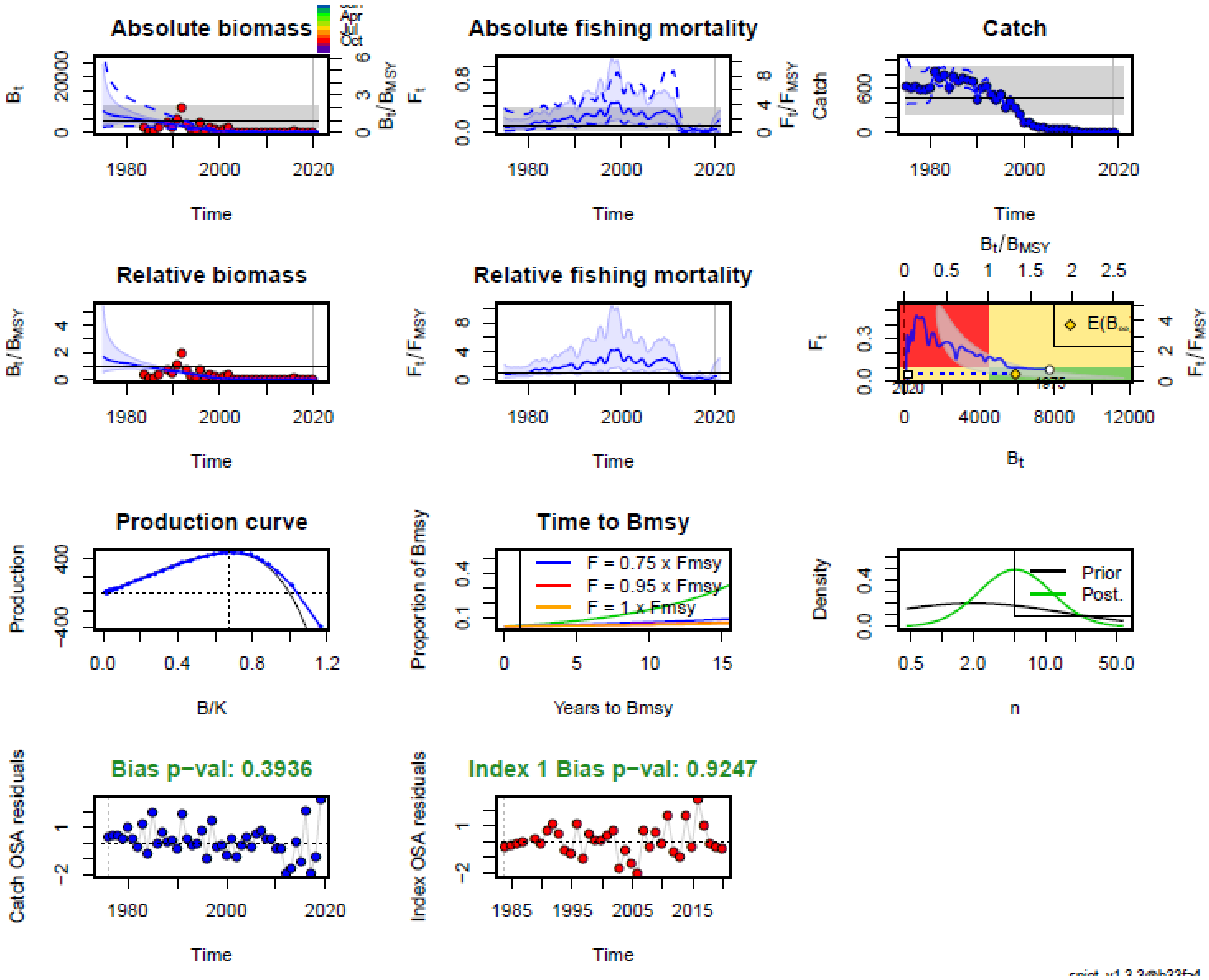


Figure 7. Results of the model fit for Scenario 2 and RUN 1.1.

SCENARIO 2
RUN 1.1

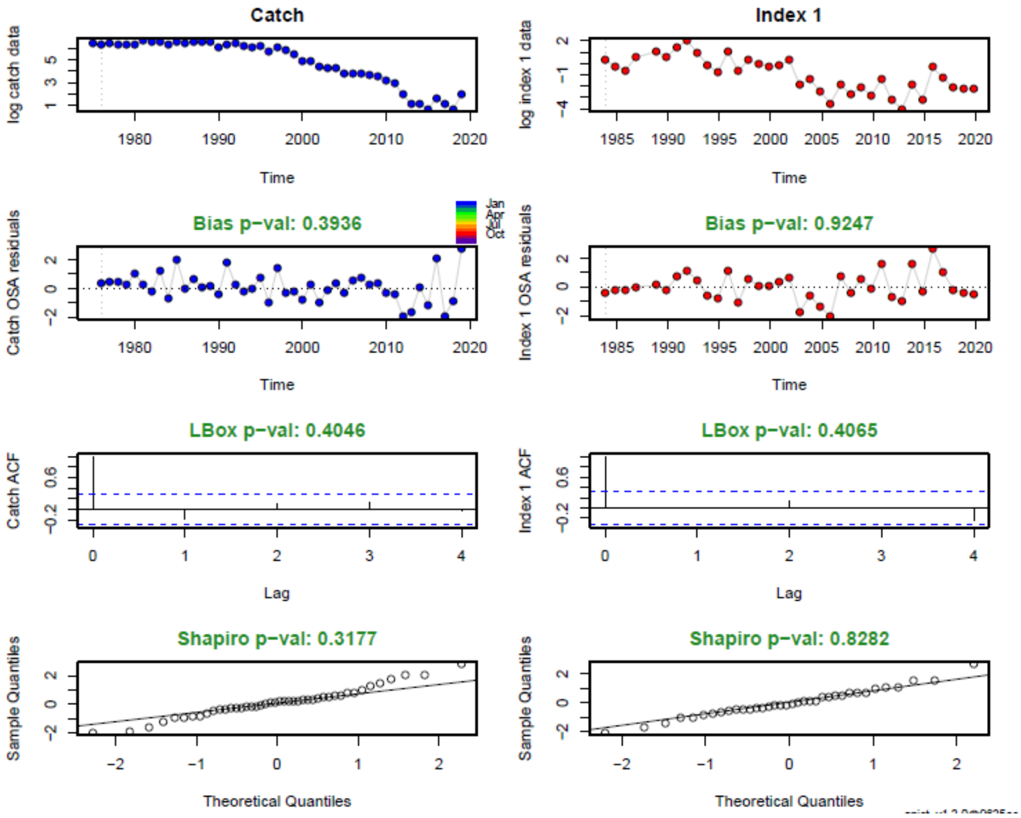


Figure 8. Result of the model diagnostic for Scenario 2 RUN 1.1.

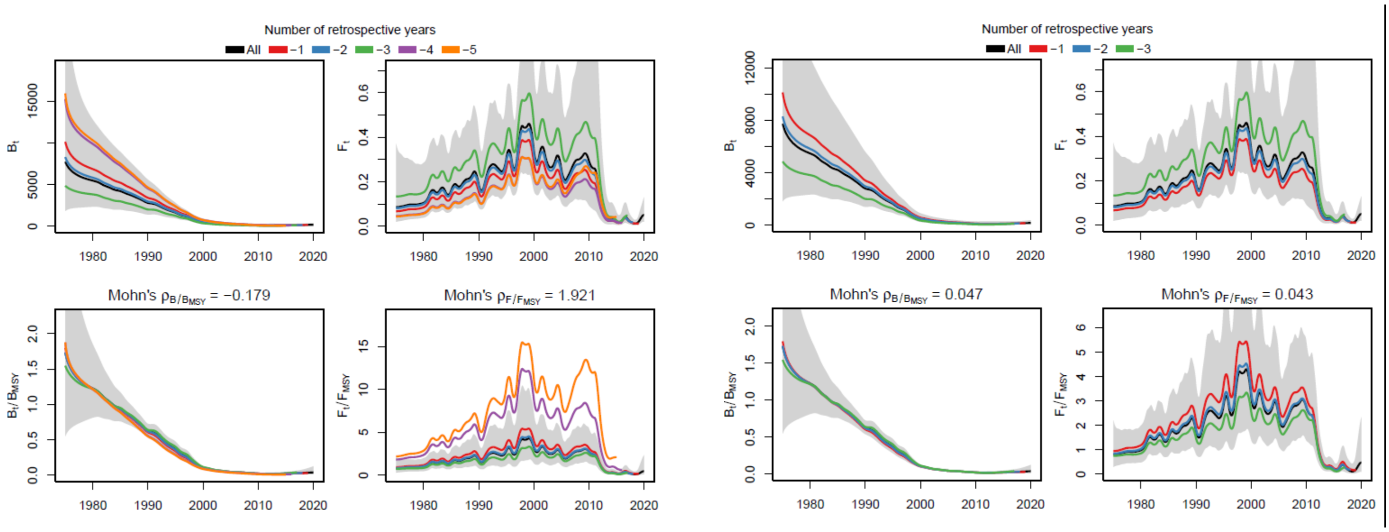


Figure 9. Retrospective analysis for Scenario 2 RUN 1.1. Left (retro (n=5)) and right (retro (n=3)).

Table 4. Results SPiCT model for Scenario 2 y RUN 2.1.

SCENARIO 2 RUN 2.1				
Summary estimates				
	estimate	**cilow**	**ciupp**	**log.est**
alpha	46.08	0.04	50571.04	3.83
beta	0.18	0.11	0.3	-1.71
r	0.16	0.05	0.54	-1.84
rc	0.16	0.05	0.54	-1.84
rold	0.16	0.05	0.54	-1.84
m	345.36	150.75	791.19	5.84
K	8680.05	3801.93	19817.13	9.07
q	0	0	0	-7.03
n	2.00	2.00	2.00	2.00
sdb	0.02	0	19.91	-4
sdf	0.51	0.39	0.66	-0.67
sdi	0.84	0.67	1.06	-0.17
sdc	0.09	0.06	0.13	-2.38
Stochastic Reference Points				
	estimate	**cilow**	**ciupp**	**log.est**
Bmsys	4335.09	1906.89	9855.35	8.37
Fmsys	0.08	0.02	0.27	-2.53
MSYs	344.6	150.26	790.33	5.84
State				
	estimate	**cilow**	**ciupp**	**log.est**
B_2019.94	192.54	88.71	417.93	5.26
F_2019.94	0.05	0.02	0.12	-3.03
B_2019.94/Bmsy	0.04	0.01	0.15	-3.11
F_2019.94/Fmsy	0.61	0.13	2.9	-0.5
Predictions				
	prediction	**cilow**	**ciupp**	**log.est**
B_2021.00	215.69	91.54	508.24	5.37
F_2021.00	0.05	0.01	0.19	-3.03
B_2021.00/Bmsy	0.05	0.01	0.19	-3
F_2021.00/Fmsy	0.61	0.09	3.95	-0.5
Catch_2020.00	9.87	4.44	21.95	2.29
E(B_inf)	6019.29	NA	NA	8.7

SCENARIO 2
RUN 2.1

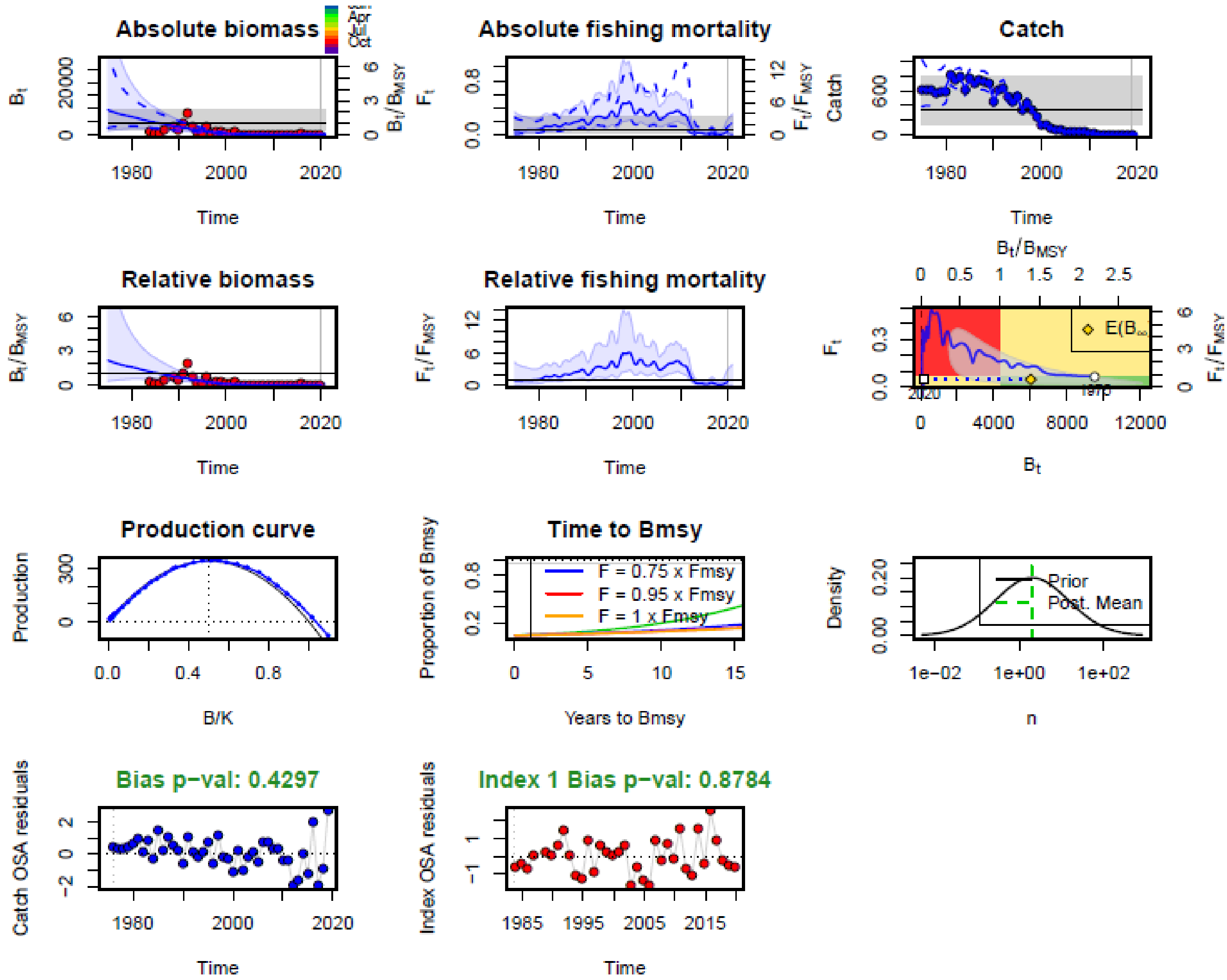


Figure 10. Results of the model fit for Scenario 2 and RUN 2.1

SCENARIO 2
RUN 2.1

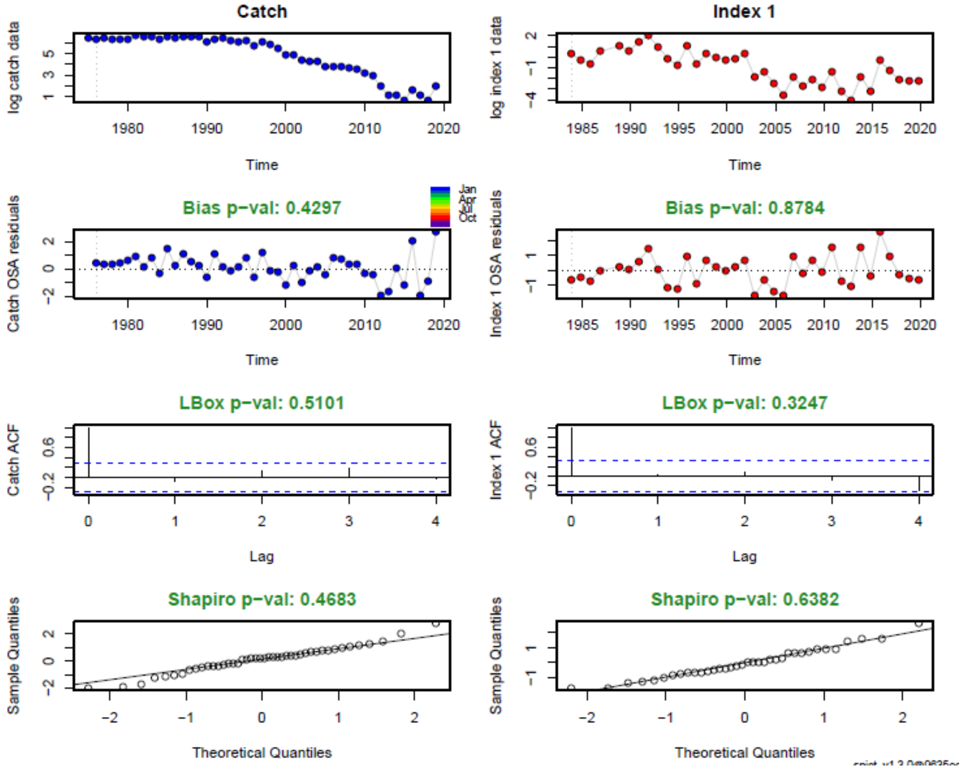


Figure 11. Result of the model diagnostic for Scenario 2 RUN 2.1

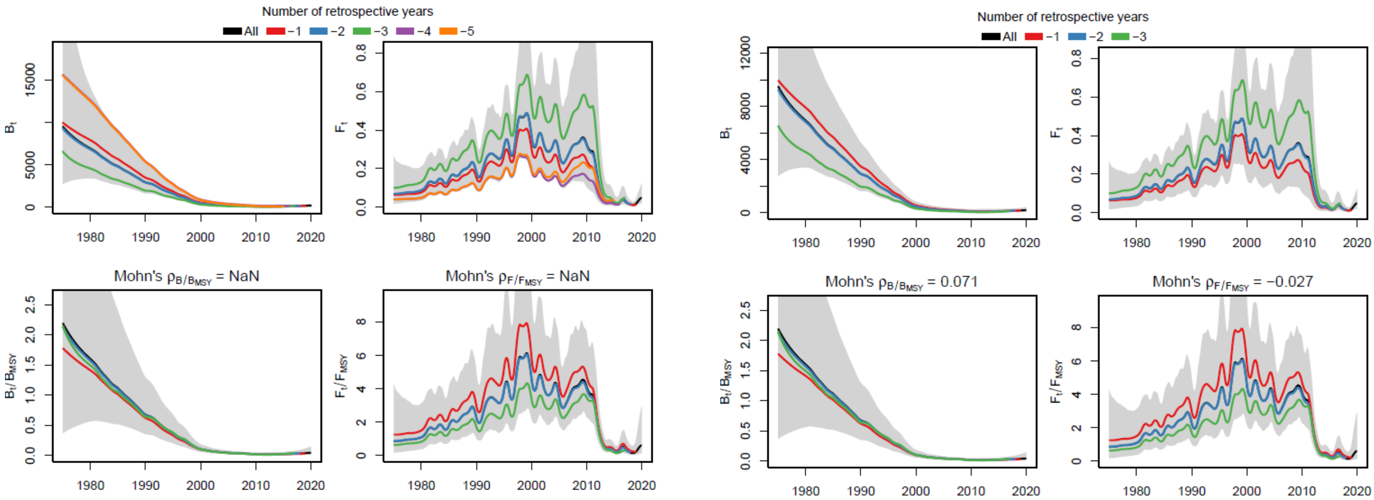


Figure 12. Retrospective analysis for Scenario 2 RUN 2.1. Left (retro (n=5)) and right (retro (n=3)).

Table 5. Results SPiCT model for Scenario 2 y RUN 3.1.

SCENARIO 2 RUN 3.1				
Summary estimates				
	estimate	**cilow**	**ciupp**	**log.est**
alpha	106.8	0.16	71797.59	4.67
beta	0.18	0.11	0.29	-1.72
r	0.3	0.07	1.23	-1.22
rc	0.21	0.07	0.61	-1.57
rold	0.16	0.05	0.47	-1.83
m	417.61	213	818.77	6.03
K	7081.55	4270.99	11741.63	8.87
q	0	0	0	-6.99
n	2.85	1.33	6.12	1.05
sdb	0.01	0	5.26	-4.85
sdf	0.51	0.39	0.66	-0.67
sdi	0.84	0.66	1.06	-0.18
sdc	0.09	0.06	0.13	-2.39
Stochastic Reference Points				
	estimate	**cilow**	**ciupp**	**log.est**
Bmsys	4021.03	2462.92	6564.85	8.3
Fmsys	0.1	0.04	0.31	-2.27
MSYs	417.42	212.79	818.85	6.03
State				
	estimate	**cilow**	**ciupp**	**log.est**
B_2019.94	186.48	85.9	404.83	5.23
F_2019.94	0.05	0.02	0.13	-2.99
B_2019.94/Bmsy	0.05	0.02	0.12	-3.07
F_2019.94/Fmsy	0.48	0.12	1.98	-0.73
	prediction	**cilow**	**ciupp**	**log.est**
B_2021.00	209.5	89.49	490.46	5.34
F_2021.00	0.05	0.01	0.2	-2.99
B_2021.00/Bmsy	0.05	0.02	0.16	-2.95
F_2021.00/Fmsy	0.48	0.08	2.78	-0.73
Catch_2020.00	9.91	4.47	21.96	2.29
E(B_inf)	5778.45	NA	NA	8.66

SCENARIO 2
RUN 3.1

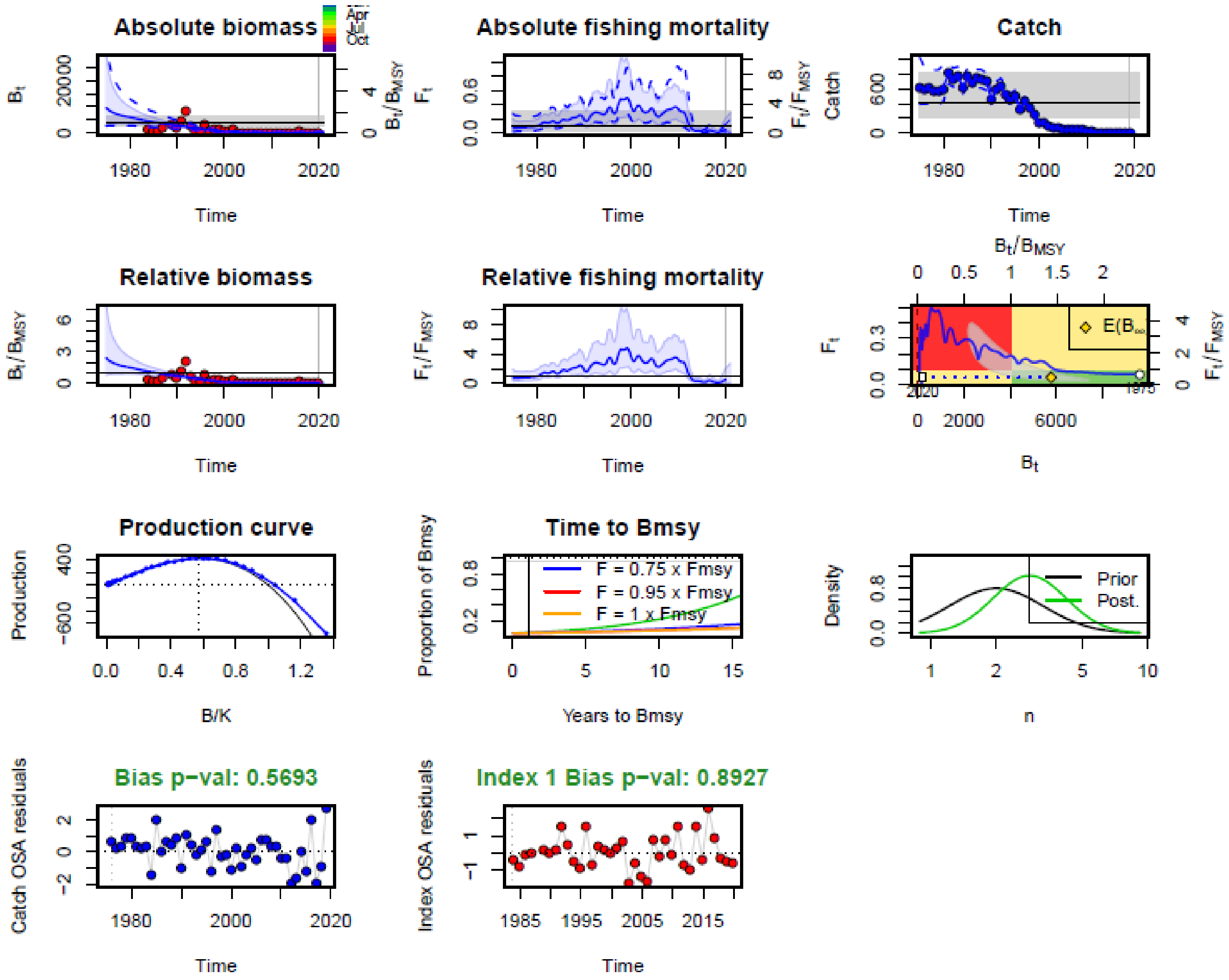


Figure 13. Results of the model fit for Scenario 2 and RUN 3.1.

SCENARIO 2
RUN 3.1

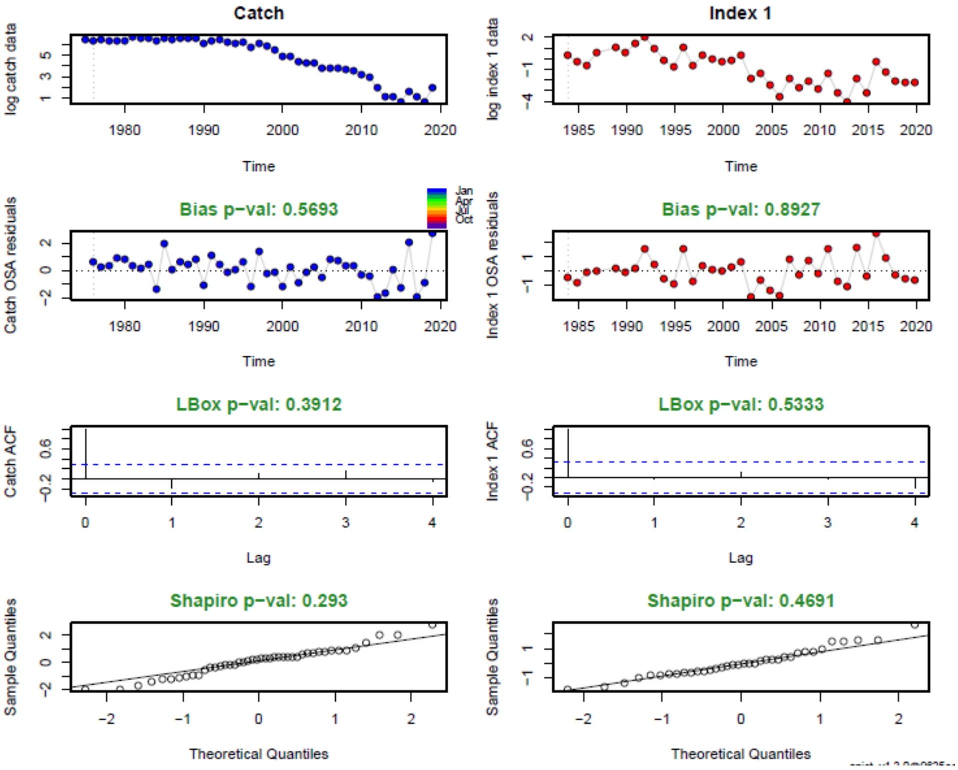


Figure 14. Result of the model diagnostic for Scenario 2 RUN 3.1

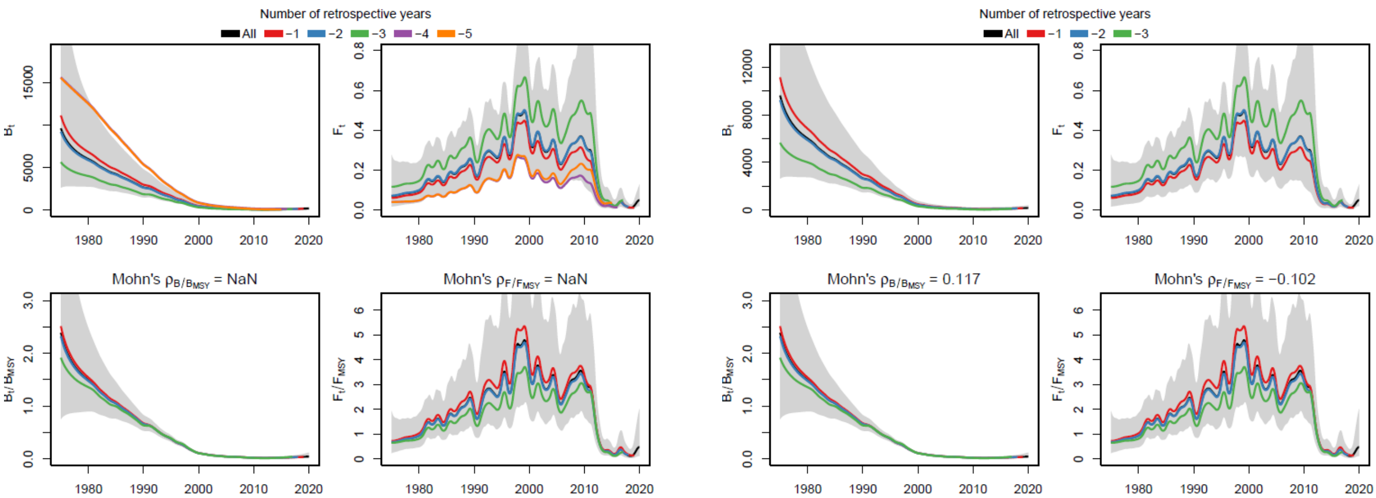


Figure 15. Retrospective analysis for Scenario 2 RUN 3.1. Left (retro (n=5)) and right (retro (n=3)).

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